PATENT
PDNO 200311281-1

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re Application of: Carl Staelin et al.	: Group Art Unit: 2861
Serial No. 10/698,667 Filed: Oct. 31, 2003	: Examiner Thinh N. Nguyen

For: **INK THICKNESS CONSISTENCY IN DIGITAL PRINTING PRESSES**

RULE 131 DECLARATION BY INVENTORS

I, the undersigned, declare that:

I am an inventor in the above-captioned patent application.

I prepared an invention disclosure entitled "A method for predicting developer voltage in an HP Indigo press" (the "Invention Disclosure"). A copy of the Invention Disclosure is attached. I signed the Invention Disclosure on April 6, 2003. The Invention Disclosure was submitted to the intellectual property department of Hewlett-Packard Company.

All statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements were made with the knowledge that willful false statements and the like may jeopardize the validity of the application or any patent issued thereon.

July 15, 2007
Date

Carl Staelin

Jul 15, 2007
Date

Ruth Bergman

Jul 15, 2007
Date

Mani Fischer

____________	____________________
Date	Darryl Greig
July 15, 2007	____________________
Date	Marie Vans
____________	____________________
Date	Gregory Braverman
____________	____________________
Date	Shlomo Harush
____________	____________________
Date	Eyal Shelef

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Date	Carl Staelin
Date	Ruth Bergman
Date	Mani Fischer

Date	Darryl Greig
Date	Marie Vans
15th of July, 2007 Date	Gregory Braverman
15/07/07 Date	Shlomo Harush
15/7/07 Date	Eyal Shelef

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Date	Carl Staelin
Date	Ruth Bergman
Date	Mani Fischer

16th July 2007 Date	Darryl Greig
Date	Marie Vans
Date	Gregory Braverman
Date	Shlomo Harush
Date	Eyal Shelef

HPL INVENTION DISCLOSURE

invent

PDNO: 200311281 DATE RCVD: 4-7-03 ATTORNEY: SEH

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Descriptive Title of Invention: A method for predicting developer voltage in an HP Indigo press

Name of Project: Indigo Systems Software Project

Product Name or Number:

Was a description of the invention published, or are you planning to publish? If so, the date(s) and publications(s):
Not yet published. It will be published internally at the HP TechCon on April 28, 2003. There are currently no plans for external publication.

Was a product including the invention announced, offered for sale, sold, or is such activity proposed? If so, the date(s) and location(s):
No.

Was the invention disclosed to anyone outside of HP, or will such disclosure occur? If so, the date(s) and name(s):
No.

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Was the invention described in a lab book or other record? If so, please identify (lab book #, etc.):
No.

Was the invention built or tested? If so, the date:
Yes. The initial laboratory research and evaluation was done in March 2003. It has not yet been prototyped or tested in a press.

Was this invention made under a government contract? If so, the agency and contract number:
No.

Description of Invention: *Please preserve all records of the invention and attach additional pages for the following. Each additional page should be signed and dated by the inventor(s) and witness(es).*

A. Description of the construction and operation of the invention (include appropriate schematic, block, & timing diagrams; drawings; samples; graphs; flowcharts; computer listings; test results; etc.).
B. Advantages of the invention over what has been done before.
C. Problems solved by the invention.
D. Prior solutions and their disadvantages (if available, attach copies of product literature, technical articles, patents, etc.).

Signature of Inventor(s): Pursuant to my (our) employment agreement, I (we) submit this disclosure on this date: April 6, 2003

Employee No.	Name	Signature	Telnet	Mailstop	Entity & Lab Name
268750	Carl Staelin			HPL-I	HPL Israel
472519	Ruth Bergman			HPL-I	HPL Israel
472520	Mani Fischer			HPL-I	HPL Israel
472512	Darryl Greig			HPL-I	HPL Israel

(If more than four inventors, include additional information on another copy of this form and attach to this document)

Signature of Witness(es): *(Please try to obtain the signature of the person(s) to whom invention was first disclosed.)*
The invention was first explained to, and understood by, me (us) on this date:

Full Name	Signature	Date of Signature
Doron Shaked		Apr 6 2003
Hila Nachlieli		Apr 6 2003

Inventor & Home Address Information: *(If more than four inventors, include addl. information on a copy of this form & attach to this document)*

Inventor's Full Name: Carl Staelin			
Street: 61 Palmach, Apt. 8			
City: Haifa		State: ISRAEL	Zip: 34973
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Carl	Citizenship: USA		

Inventor's Full Name: Ruth Bergman			
Street: 45 Laskov Street			
City: Haifa		State: ISRAEL	Zip: 34950
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Ruth	Citizenship: USA & Israel		

Inventor's Full Name: Mani Fischer			
Street: Taverski 7			
City: Haifa		State: Israel	Zip:
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Mani	Citizenship: Israel		

Inventor's Full Name: Darryl Greig			
Street: HaHorsha 9, Center Carmel			
City: Haifa		State: ISRAEL	Zip: 34524
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Darryl	Citizenship: Australia		

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A. Description of the construction and operation of the invention (include appropriate schematic, block, & timing diagrams; drawings; samples; graphs; flowcharts; computer listings; test results; etc).

See the attached technical report describing both the related problem of dot gain table prediction and this problem. The dot gain prediction was covered by a previous invention disclosure.

B. Advantages of the invention over what has been done before (specifics as to why this approach is better than previous solutions).

Previously the developer voltage was always set using a process that required printing pages and measuring the result. Consequently, it wasn't done very often, and since the state of the press drifts over time, this can result in poor color control. The advantage of this method is that it does not require printing pages, with the tradeoff that the prediction is not as accurate as a measured value. However, the predictions are more accurate than the current method of sparse measurements for most of the time.

C. Problems solved by the invention (description of the existing problems that this invention addresses).

If the developer voltage is not controlled properly, then the press cannot adequately control the resulting prints, so prints that are supposed to be identical can be visually different. This allows for more continuous control of the developer voltage in a non-intrusive fashion, hopefully resulting in improved print quality and consistency.

D. Prior solutions and their disadvantages (describe what others have done and the shortcomings of these solutions; if available, attach copies of product literature, technical articles, patents, etc.).

HPL INVENTION DISCLOSURE

invent

PDNO: DATE RCVD: ATTORNEY:

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Signature of Inventor(s): Pursuant to my (our) employment agreement, I (we) submit this disclosure on this date: April 6, 2003

Employee No.	Name	Signature	Telnet	Mailstop	Entity & Lab Name
372032	Marie Vans	M. Marie Vans		HPL-I	HPL Israel
36446910	Gregory Braverman	[signature]			HP Indigo
35983580	Shlomo Harush	[signature]			HP Indigo
36446800	Eyal Shelef	[signature]			HP Indigo

(If more than four inventors, include additional information on another copy of this form and attach to this document)

Signature of Witness(es): *(Please try to obtain the signature of the person(s) to whom invention was first disclosed.)*

The invention was first explained to, and understood by, me (us) on this date:

Full Name	Signature	Date of Signature
Orron Shaked		Apr 6, 2003

Inventor & Home Address Information: *(If more than four inventors, include addl. information on a copy of this form & attach to this document)*

Inventor's Full Name: Marie Vans			
Street: Elein 1			
City: Shefar-am		State: ISRAEL	Zip: 20200
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Marie	Citizenship: USA		

Inventor's Full Name: Gregory Braverman			
Street: Mavo Hatikhon 8, Apt. 1			
City: Ramat Gan		State: ISRAEL	Zip: 52345
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Gregory	Citizenship: Israel		

Inventor's Full Name: Shlomo Harush			
Street: 5 Eliyahu Miron Street, Apt. 8			
City: Nes-Ziyona		State: ISRAEL	Zip:
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Shlomo	Citizenship: Israel		

Inventor's Full Name: Eyal Shelef			
Street: HaYarden 13, Apt. 7			
City: Tel Aviv		State: ISRAEL	Zip:
Do you have a Residential P.O. Address? P.O. Box	City	State	Zip
Greeted as *(nickname, middle name, etc.)*: Eyal	Citizenship: Israel		

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Dot gain table and developer voltage prediction for the HP Indigo press

Carl Staelin, Ruth Bergman, Mani Fischer, Darryl Greig, Marie Vans
Hewlett-Packard Laboratories Israel

Gregory Braverman, Shlomo Harush, and Eyal Shelef
HP Indigo

6th April 2003

Abstract

Color consistency is crucial for both photo and commercial printing applications. Dot gain tables are currently updated sporadically, and between updates colors can shift due to process drift in the press. The goal is to dynamically control the dot gain table and developer voltage to ensure more consistent color control while minimizing waste and calibration measurements.

Treating the problem as a machine-learning problem, we predict the dot gain table values given the current state of the machine, as expressed in the values of nineteen sensor measurements. Our initial investigation based on a preliminary dataset shows that linear regression methods can predict the dot gain values with acceptable accuracy.

1 Introduction

Color consistency is crucial for both photo and commercial printing applications. Dot gain tables are currently updated sporadically, and between updates colors can shift due to process drift in the press. The goal is to dynamically control the dot gain table and developer voltage to ensure more consistent color control while minimizing waste and calibration measurements.

Currently the dot gain table and developer voltage are controlled by sporadically printing special calibration jobs that print test patterns that can be observed and whose characteristics can be measured by the press. The calibration process first prints one or more test patterns with 100% ink coverage that are used to find the proper developer voltage setting for each ink in order for the ink thickness at 100% coverage to be correct. Once the developer voltage is set, the actual ink thickness or optical density at 100% coverage is measured. Then the calibration process prints one or more sheets of test patterns with monochromatic swatches of uniform digital dot area to measure the physical dot area for each of the digital dot areas.

Broadly speaking there are two separate machine learning problems: (1) predict the developer voltage and corresponding ink optical density at 100% coverage per ink given the current machine state, and (2) predict the dot gain table values for each digital dot area of interest for each ink given the current machine state, developer voltage, and ink optical density at 100% coverage. There are a number of possible related problems, such as predicting the dot gain table values for one screen, given the current dot gain values from a second screen.A large number of machine learning regression algorithms are applicable to these problems. We evaluate the accuracy of three common methods: artificial Neural Networks (NN), Support Vector Machines (SVM), and linear regression.

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If a method is found to supply sufficiently accurate predictions, we can replace or augment the calibration procedure with a prediction-based process that has much less impact on customer workflow and consumable usage. The minimal requirements for the Indigo press are that the absolute difference between the predicted dot area and physical dot area is less than 2 at least 67% of the time, and less than 5 at least 95% of the time, for all digital dot areas.

In order to achieve color accuracy and consistency the dot area must be accurate. To ensure that the requested dot area is printed, the HP Indigo press uses a dot gain look up table (LUT) to map the digital dot area to the actual printed dot area. To maintain color accuracy, a calibration procedure is performed, during which time the physical dot area is measured for each of various digital dot areas. This procedure consumes substrate, ink and time, which prevents frequent updates. Unfortunately, the dot gain table is only accurate at the time of measurement because the press is not static. Consequently, the dot size is not properly controlled and can fluctuate between measurements, potentially causing color consistency and image quality problems.

The dot gain is defined in Equation 1.

$$dot\,gain = \frac{printed\,dot\,area}{digital\,dot\,area} \qquad (1)$$

Both the digital dot area and printed dot area are expressed as a percentage of the area that is covered, where 100 means that the whole area is covered with ink. The dot gain table contains the printed dot area value from Equation 1 for each digital dot area of interest.

The calibration process uses an inline optical densitometer to read the physical dot areas from a swatch of uniform density in a single color. Given various physical constraints, one may fit up to fifteen such swatches on a single sheet. Since the presses can have up to seven separations (inks), this implies that we may measure up to two digital dot areas for each separation in a single sheet.

As an alternative to the full calibration process, we might create a "fast calibration" process that measures two points per color separation, and then uses the measured information and the machine state to predict the rest of the dot gain lookup table values.

We analyzed a dataset of dot gain LUT's collected by HP Indigo. Our results for this dataset are promising, and, in particular, are within the required limits. It is important, however, to keep in mind that this dataset is small by machine learning standards - approximately 130 samples for each screen and separation.

2 The Printing Process

Converting a digital signal to a physical dot on a piece of paper is an analog process that can be affected by any number of system elements and interactions. The process of image production consists of three stages (see Figure 1):

1. Image generation — A latent image is created on the PIP foil. The PIP foil includes photoconductive material. When exposed to light, this material becomes a conductor. The PIP is negatively charged by the Scorotron assembly. A laser beam originating from the Writing Head is used to discharge specific areas on the PIP foil. These discharged areas comprise the latent image.

2. Image development — During this stage the latent image is developed by ink on the PIP. The ElectroInk consists of small colored ink particles that are electrically charged. The BID (Binary Ink Development) units apply developed ink onto the discharged areas that compose the latent image on the PIP foil.

3. Image transfer — During this stage the developed image is transferred from the PIP to the Blanket that wraps the ITM. The image is then transferred from the Blanket to the substrate. The transfer of the developed image from the PIP to the Blanket is achieved through electrical and mechanical forces. The Blanket is positively charged and is heated to about 100°C. This raises the temperature of the ink film on the Blanket that causes the ink particles to swell and

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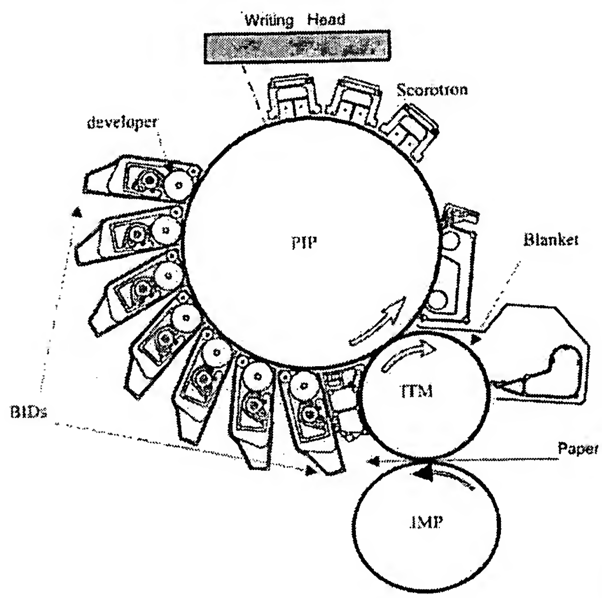
Figure 1: Indigo Press



to acquire a gelatin-like form. At this stage, the developed image is transferred from the Blanket to the substrate.

Many key elements, such as the PIP foil and blanket are regularly replaced and each replacement part has its own characteristics. Thus, it is likely that a full dot gain table measurement will need to be taken after each major part replacement. In addition, during normal operation other parameters, such as temperature, vary continuously.

For our purposes, the HP Indigo press has twenty-four observable parameters.

Table 1 shows the list of observed parameters whose values are available to the dot gain table control system. Some of the parameters are properties of physical devices, such as the blanket, PIP, ink batch, and corona.

According to HP Indigo the most important parameters (while using a constant substrate) are probably: developer voltage, ink separation, ink den-

Table 1: Indigo Press Parameters

Type	Parameter	Min	Max
Ink	density*	1.69	2.36
	conductivity*	67	123
	temperature	28.83	31.6
	separation*	-	-
Imaging oil	temperature	18.16	21.03
	dirtiness	1.272	1.316
ITM	temperature	126.7	135.1
	blanket counter*	66	58207
PIP	PIP counter*	46	86334
	vlight/vbackground*	34	90
	background qualifier	-43	149
Process	developer voltage*	-494.9	-345.7
	vcorona	-6092	-5858
	icorona	1.91	2.33
	vgrid	-887.2	-540.6
	igrid	-1.55	-1.07
	impression counter	1285003	1376710
	time and date	-	-
	corona age	-	-
	optical density 100%	1.05	1.8
	machine temperature	22.25	28.24
Other	screen*	-	-

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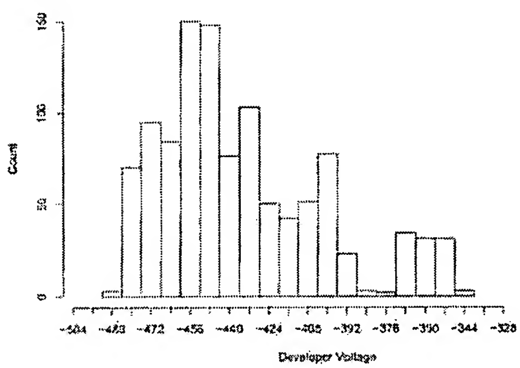
Figure 2: Histogram of Developer Voltage Values



sity, ink conductivity, blanket counter, screen, PIP counter, and PIP v-light/v-background. These are marked with an asterisk in Table 1.

During normal operation many of the parameters, such as the temperatures, are relatively stable. Some parameters, such as the various counters, change continuously while other parameters, such as the developer voltage, are used to control aspects of the printing process and generally vary within a standard operating range.

The developer voltage for this dataset (collected from a Series 1 machine) is adjusted in steps of 8 volts, although the final recorded voltage has some noise. A histogram of the total developer voltage observations separated into 8-volt bins is given in Figure 2. The distribution of the developer voltage values in this dataset appears to be bimodal, with the main mode occurring at -456, and a secondary mode at about -360. The extreme values in the bin centered on -488 and the bin centered on -344 are very underrepresented, as are the bins -384 and -376, between the two modes.

3 Machine learning methods

We used three methods for predicting the dot gain tables: linear regression, neural networks, and support vector machines. Both neural networks and support vector machines fit non-linear multivariate functions to the training data. The fitting and analysis for each method was done using the R statistical package, a GNU software platform that largely re-implements the commercial package S-Plus.

3.1 Support vector machines

Support vector machines are a kernel-based approach to machine learning. A good tutorial introduction to SVM was written by Burges[1]. Other standard references on SVM include Vapnick[2] and Cristianini[3]. From Platt [4]the definition of the quadratic programming problem that for support vector learning is shown in Equation 2:

$$max_\alpha W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j k(\vec{x_i}, \vec{x_j})\alpha_i\alpha_j$$

$$0 \leq \alpha_i \leq C, \forall i \tag{2}$$

$$\sum_{i=1}^{l} y_i \alpha_t = 0$$

where l is the number of (x, y)samples, $k(\vec{x_i}, \vec{x_j})$ is the kernel function of two sample input vectors $\vec{x_i}$ and $\vec{x_j}$, $y_i$and $y_j$are the corresponding sample values, C is a given parameter, and $\alpha_i$are being optimized by the training process.

The quadratic programming problem is solved if and only if the Karush-Kuhn-Tucker (KTT) conditions are fulfilled and $Q_{ij} = y_i y_j k(\vec{x_i}, \vec{x_j})$is positive semi-definite.

We used the radial basis function (RBF) kernel, where $k(\vec{u}, \vec{v}) = e^{-\gamma|\vec{u}-\vec{v}|^2}$. To train an SVM machine with the RBF kernel, one must select two meta-parameter values: C and γ. We use a design-of-experiments (DOE) based method with cross-validation error estimation to select the best parameter settings for each problem as described in

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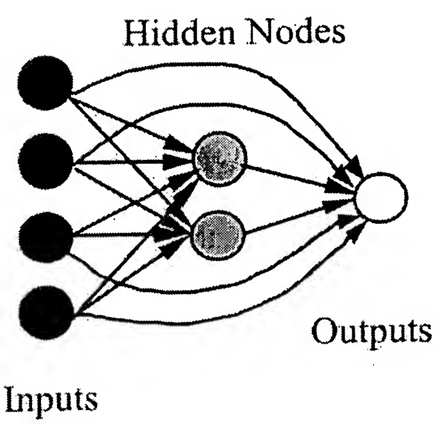
Figure 3: Feedforward NN Architecture



Staelin[5]. The SVM models are trained using *libsvm* library[6], with an R interface supplied by the *e1071* package.

3.2 Artificial neural networks

Neural networks are a well-known technique for machine learning. A good introduction and description can be found in Bishop[7]. We used the neural network package *nnet* from R. The *nnet* package uses standard feed-forward neural network architecture with a single hidden layer and logistic activation functions. The networks are fitted using BFGS quasi-Newton optimization, with the gradients supplied by backpropagation.

In this architecture, each input node is connected to each of the hidden nodes, and we allow linear (skip) connections between the input nodes and the output node. The output node is set to have linear activation. Each hidden node is connected to the output node, as in Figure 2. We represent the connection weight between node i and node j by w_{ij}. Each network node is indexed: index 0 is a bias input with constant value 1, indices $1, \ldots, N_{in}$ are the input nodes, indices $(N_{in}+1), \ldots, (N_{in}+N_{hid})$ are the hidden nodes, and $N_{in}+N_{hid}+1$ is the output node. If no connection exists between nodes i and j, then w_{ij} is fixed as a constant 0.

Let x_i be the input to any node i: input, hidden or output, and z_i the output from that node. The input and output for the input nodes are identical. The input and output functions for hidden node i in terms of previous hidden nodes and inputs are shown in Equations 3 and 4 respectively. Since we use linear output nodes, the output z_i for output node $i = N_{in}+N_{hid}+1$ is just x_i.

$$x_i = \sum_{j=0}^{i-1} w_{ij} z_j \tag{3}$$

$$z_j = \frac{e^{x_j}}{1 - e^{x_j}} \tag{4}$$

For our experiments we used 2 hidden nodes, and fitted the networks using weight decay regularization (see [7]) with decay parameter 0.001.

4 Results

Our analysis is based on a dataset collected by HP Indigo in early February over a one week period on a single Series I Indigo Press by a single operator using the automatic calibration process. The dataset contains 269 dot gain tables each containing fifteen (15) physical dot area values for each of the four inks and labelled with all the parameters appearing in Table 1. There are measurements for two screens, 136 tables for HDI-175, and 133 tables for Sequin.

4.1 Dot gain machine learning problems

The first and most important question was whether it is possible to predict the dot gain lookup table values with sufficient accuracy just given the current state of the machine, including the measured developer voltage and OD100 parameters.

Given the current state of the machine and a screen, we want to predict the physical dot area for each of n separations and m digital dot areas, in order to fully populate the dot gain lookup tables. We can

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formulate the problem in several ways. One possibility is to create a single monolithic machine-learning problem where the state of the machine, the selected screen, the separation, and digital dot area are all included as inputs, and the physical dot area is the output. At the other extreme, one may create separate machine learning problems for each combination of screen, separation, and digital dot area, with the machine state as input and the physical dot area as output. There are a variety of intermediate formulations that create separate machine learning problems incorporating the screen, separation, and digital dot area as inputs. These formulations trade off problem complexity with the number of models trained.

We attempted several different intermediate problem formulations. In the first, we solve separately for each color separation, digital dot size, and screen, giving $n \cdot m \cdot s$ distinct models or functions, where n is the number of color separations, m is the number of sampled digital dot sizes, and s are the screens. The second is to solve separately each color separation and screen, resulting in $n \cdot s$ models. Results from tests using the second type of problem were not promising so we report only on tests using the first formulation.

Using "fast calibration" for two physical dot area measurements, we can pose an additional learning problem where the inputs include the device parameters as well as the two measured physical dot areas and the output is the dot gain area. For this problem, we again have a choice of the problem formulations above, and we selected the formulation that worked best in the first set of tests. We also have a number of choices with respect to the selection of points to include as the physical dot area inputs. We can select to use one or two points as input, and each of these points can be selected from the fifteen dot areas in the LUT. We tested all possible one point inputs and promising combinations of two point inputs, but report results only for one combination per separation.

We looked at a few of the possible problem formulations and found that the best solution was to have a separate machine learning problem for each screen, separation, and digital dot area. Combining problems always reduced the system accuracy, so we report results for this problem formulation only. For a single screen using four inks with fifteen digital dot areas this results in sixty independent machine learning problems.

We use 10-fold cross validation to evaluate the expected prediction error. Note that SVM repeats its parameter search algorithm for each fold, so the test data in each fold is not included in the training data used by the parameter search.

The prediction errors are the difference between the true printed dot area and the predicted print dot area. The mean error for all tests are very close to zero indicating that the predictions are unbiased. We analyzed the prediction errors using a Chi-squared goodness of fit test and found that they are approximately normally distributed. Therefore, we can use the standard methods for computing the confidence intervals.

The graphs in Figure 4 show the 67% prediction error confidence intervals for the 175lpi HDI-175 screen for each of the three machine learning methods: linear regression, neural networks, and support vector machines as a function of the digital dot area. Note that each ink behaves slightly differently.

Figure 5 shows the analogous graphs for the lower resolution screen 120lpi screen Sequin.

From the results in Figures 4 and 5, it is apparent that the behavior of all methods is similar. This means that the prediction of "hard" points is invariant of the learning method. Since linear regression performs comparably to the more complex non-linear methods, all further analysis was done using linear regression.

Figure 6 shows the 95% confidence intervals for each ink for both the HDI-175 and Sequin screens. In all cases, the 95% confidence interval is smaller than 4, which is better than the minimal requirement of a 95% confidence interval of 5. The 67% confidence intervals can be seen from Figures 4 and 5, and they are always less than 2. Clearly, the requirement of at least 67% of errors less than 2 is also met.

4.2 Dot gain prediction using two measured points

Next we analyzed the impact of adding two measured points might have on prediction accuracy. The first

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Figure 4: Prediction Error 67% Confidence Interval, HDI-175 Screen.

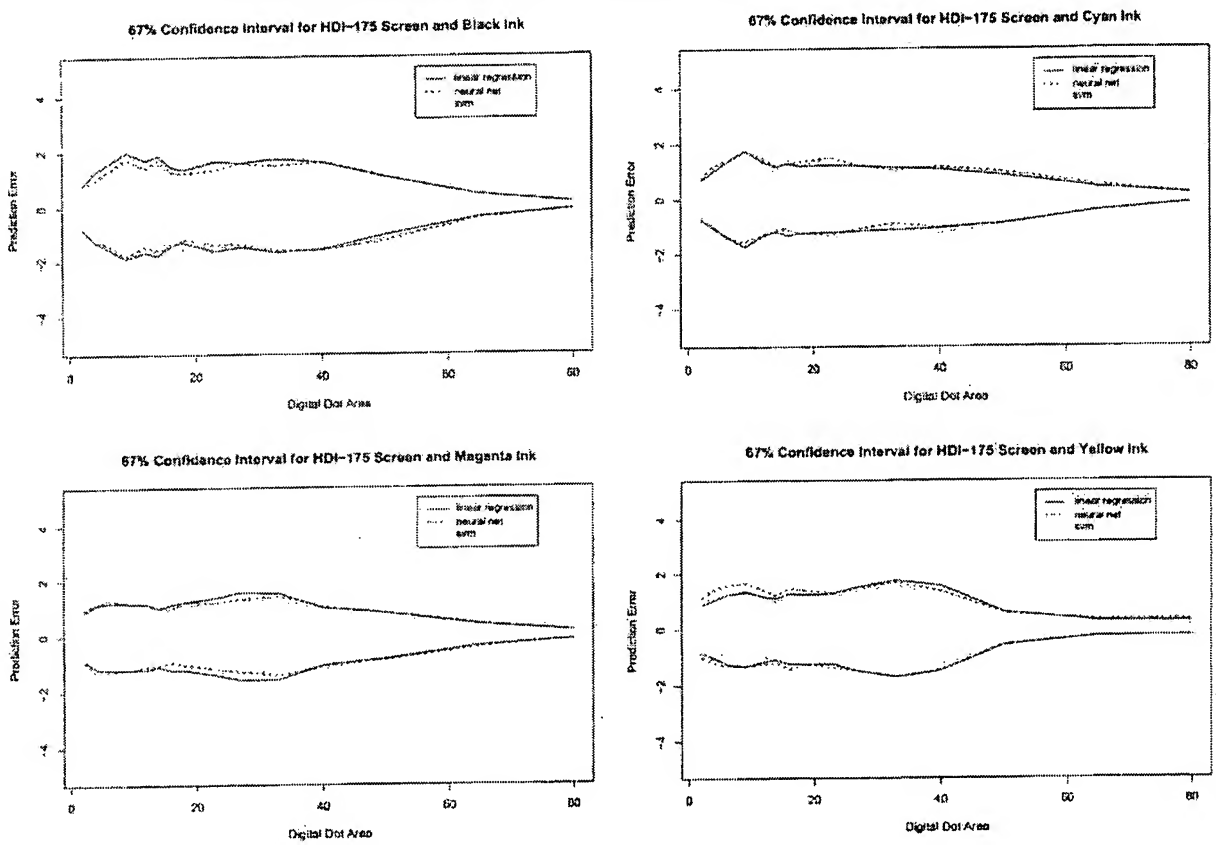

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Figure 5: Prediction Error 67% Confidence Interval, Sequin Screen

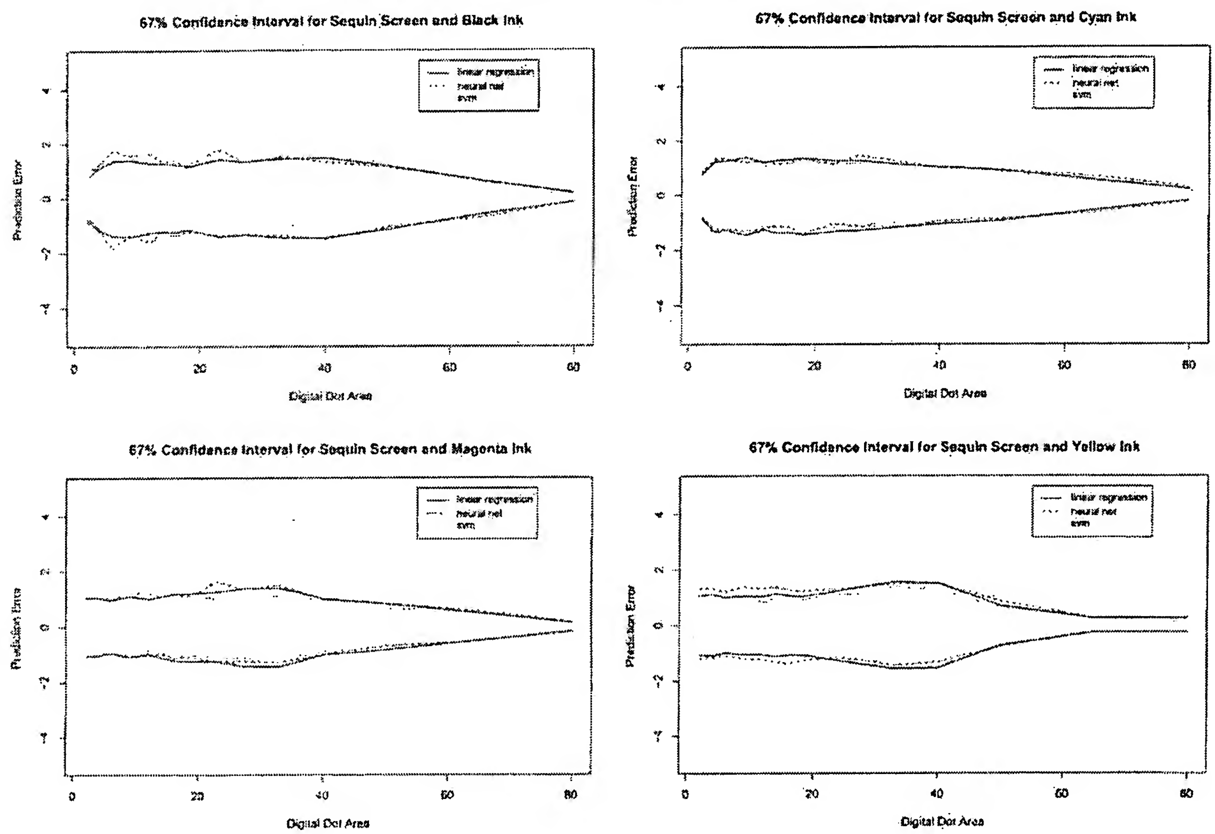

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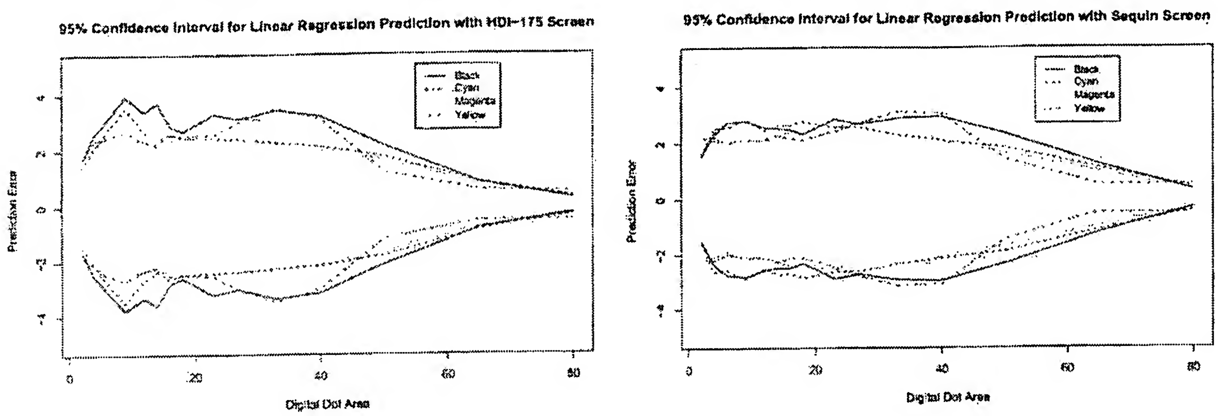
Figure 6: Prediction Error 95% Confidence Intervals for Linear Regression



stage was deciding which two points to add. After an evaluation process it was found that measuring the physical dot area at digital dot areas 23 and 40 yielded the best performance improvement for HDI-175, and digital dot areas 16 and 40 yielded the best improvement for Sequin.

Figure 7 shows the 67% and 95% prediction confidence intervals for HDI-175 and Sequin with two measured points at 23 and 40 for HDI-175 and 16 and 40 for Sequin. In all cases, the 67% and 95% confidence intervals are reduced, sometimes markedly. The process of obtaining the measurements is not ideal, as it requires the operator to interact with the press to get the measurements. However, a full calibration requires many sheets of paper (e.g. 15 sheets for 7 inks) to measure all points while a single sheet is required to collect the data for two points.

4.3 Dot gain variation over time

In order to deploy dot gain prediction effectively, we need to know how often the tables should be updated. If the tables are updated too frequently, then the color consistency can be reduced because the table values are changing much faster than the underlying physical process. If the tables are updated too infrequently, then the press can drift out of control and color consistency is again reduced. The goal is to update the dot gain tables when it is likely that the press is drifting out of control.

As a first step we must determine how fast the press drifts as a function of the number of impressions. To do this we look at the dataset as a time series and compare the measured dot gain values for each LUT with the dot gain values for each subsequent LUT and look at the resulting data as a function of LUT change versus the intervening impression count.

Figure 8 shows how the LUT table entries vary between measurements as a function of the number of intervening impressions. More precisely, it shows the standard deviation for changes in the LUT values. Since LUTs were not taken at fixed intervals, in terms of impressions, we binned the data into 500-impression buckets. Clearly the system can drift fairly quickly, so updating the LUTs as frequently as every thousand impressions would likely improve the color constancy.

One caveat with the results in Figure 8 is that the developer voltage is adjusted as the first step in the calibration process, so between each measurement the develop voltage is updated. During normal operation, the developer voltage would not be updated so frequently, so the actual variation in LUT values may be smaller than this graph indicates.

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Figure 7: Prediction Error Confidence Intervals for Linear Regression When Given Two Measured Points

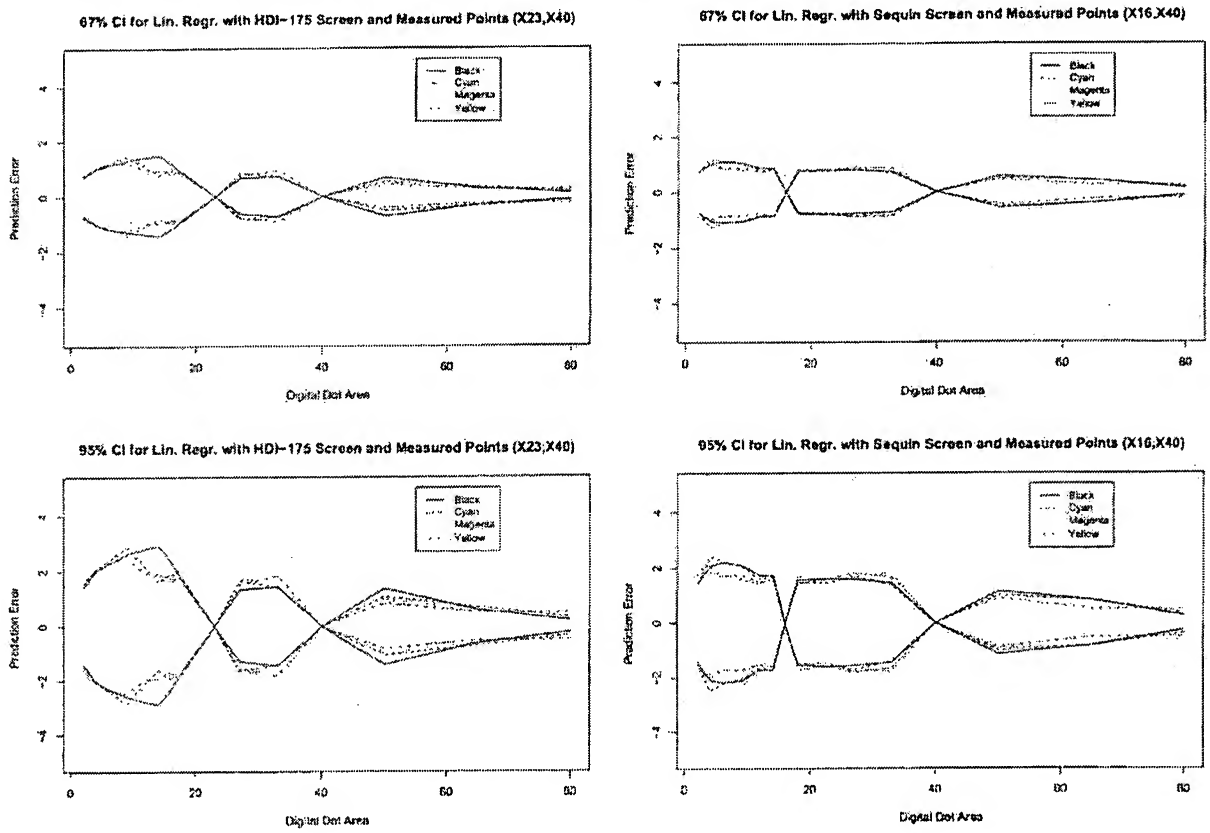

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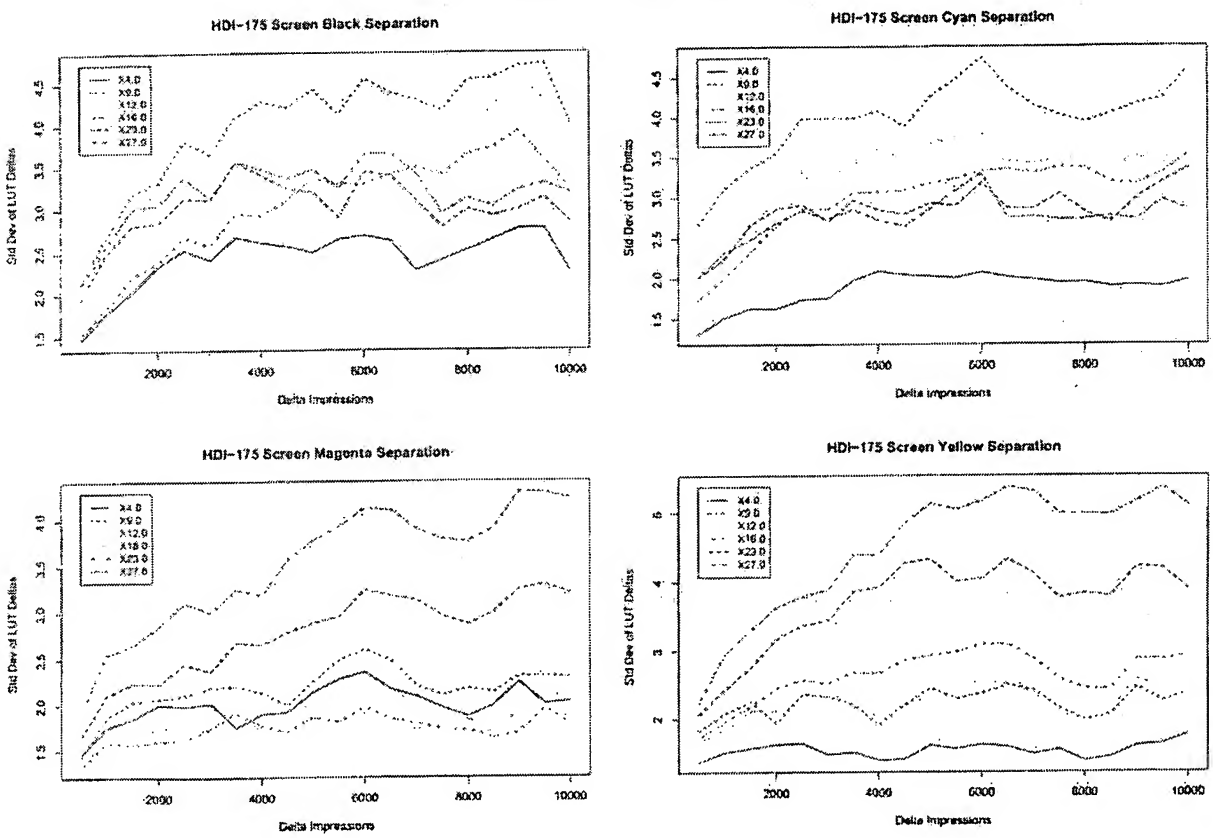
Figure 8: Standard Deviation of Physical Dot Area Differences



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4.4 Dot gain prediction parameter selection

The importance of a parameter may be measured by the effect of removing that parameter from the model. If the predictive power of the model is unaffected (or even improved) we may conclude that the parameter is not significant. On the other hand, if the model has a significant degradation in performance without a particular parameter, we may conclude that this parameter is significant and should be retained.

To implement this method we proceeded in the following manner. Firstly, for each statistical learning technique tested, model predictions were obtained for the entire dataset using the whole set of predictors. The predictions were obtained using the same 10-fold cross validation technique described in [4]. That is, for each of 10 folds of the dataset, a model was fitted to the remaining 9/10 of the data, and a prediction made on the 1/10 excluded from the fitting. This prediction is taken as the model prediction on that portion of the dataset. The procedure is carried at on each slice of that dataset until a prediction is obtained on the whole dataset.

The sum of squared errors (SSE) of these predictions was computed on each of the digital dot values of the LUTs, where both screens and all separations were included in this sum. Then similar predictions and SSE computations were made for models fitted excluding each of the input parameters in order. At the end of this, we have a matrix a row for each input parameter, and a single row for the model including all parameters, and a column for each digital dot area (DDA) value. The matrix entries are the SSE values of the model prediction on the relevant DDA, where the model used to predict excludes the input parameter corresponding to that row. The matrix rows resemble the sample in Table 2, where the rows and columns stretch over the full range of input parameters and DDA values respectively.

We repeat this experiment 20 times and from this we are able to estimate the mean and standard deviation of the SSE value for each of the table entries. Using these estimates we are able to generate confidence intervals for the differences of means between the original (full) model and each of the depleted models, for each DDA value.

Figure 9 summarizes these results. The error bars give the 95% confidence interval for the mean of the relevant depleted model SSE minus the mean of the full model SSE. If the confidence interval does not include the zero line in a particular case, then we can conclude (at the 0.05 level) that the parameter under consideration is relevant for the dot gain LUT prediction. From the graphs in Figure 9, we obtain the following categorization of the model parameters:

Significant parameters: *blanket.counter, vlight, background.qualifier, OD100, vcorona, vdeveloper, itm.temp, oil.dirt, ink.conductivity, ink.density.*

Not significant parameters: *vgrid, igrid, icorona, machine.temp, oil.temp, ink.temp.*

These results are obtained by deleting one parameter and recomputing, so they must be applied with some caution. For example, there may be two highly correlated parameters, in which case deleting one of them would not significantly affect the model, but deleting both may reduce the model accuracy. We shall consider the order of parameter deletion and possible correlations in the next section.

Note also that the significant parameters are effective at different DDA values. The blanket.counter, vlight, itm.temp variables are effective mostly at the lower DDA values. OD100, background.qualifier, ink.conductivity are effective in the mid range, and vcorona, vdeveloper, oil.dirt and ink.density have the biggest effect at the high range of DDA values. This behavior does make it difficult to rank the significant parameters, since the final ranking will depend on which range of the dot gain LUT is considered more important, and whether a comparatively small error over a wide range of values is preferable to a large error over a small range of values. In the following ranking I assume that all DDA values are equally significant, and the goal is to minimize the maximum absolute error. The most important parameters are ranked 1, the least important significant parameters are ranked 4, and the insignificant parameters are ranked 5.

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Table 2: Sample SSE matrix for DDA model predictions

	X2	X4	X6	X9	X12	X14
all	825.3441	1499.899	1759.544	2342.148	1786.486	1855.435
-blanket.counter	935.4560	1729.036	2025.373	2707.947	1929.873	1917.133
-vlight	857.9499	1463.702	1828.056	2375.569	1823.233	1838.971
-background.qualifier	862.4410	1518.113	1819.945	2480.031	1886.576	1845.397
-OD100	843.5559	1497.256	1821.808	2363.896	1895.075	1996.277
-vgrid	859.4362	1451.960	1773.247	2281.338	1766.356	1761.680
-igrid	814.0722	1449.212	1758.089	2345.243	1768.262	1789.235
-vcorona	866.6734	1502.491	1826.697	2440.609	1808.491	1941.426
-icorona	814.5600	1436.776	1726.267	2271.425	1758.439	1797.152
-vdeveloper	843.0000	1500.752	1822.115	2440.976	1795.174	1886.793

Figure 9: Difference of means 95% confidence intervals for depleted versus full linear regression models.

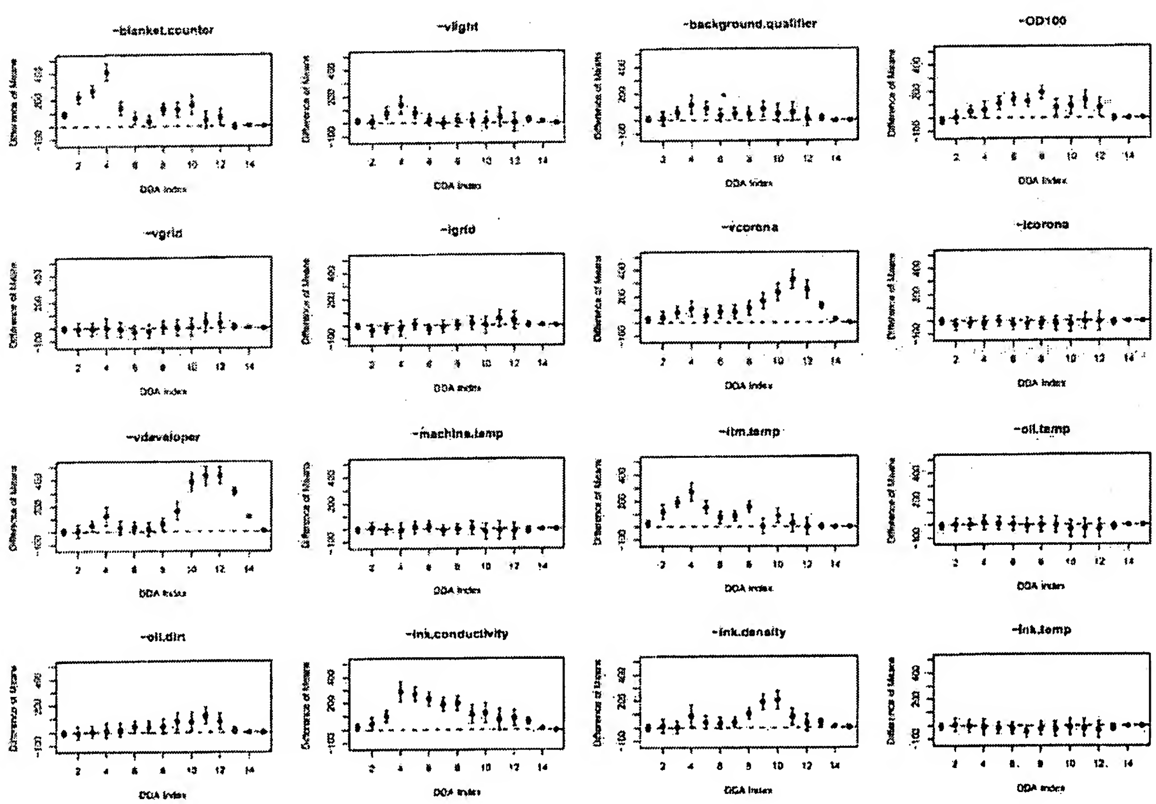

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Figure 10: Difference of means 95% confidence intervals for linear regression model depleted of all rank 5 parameters against full model

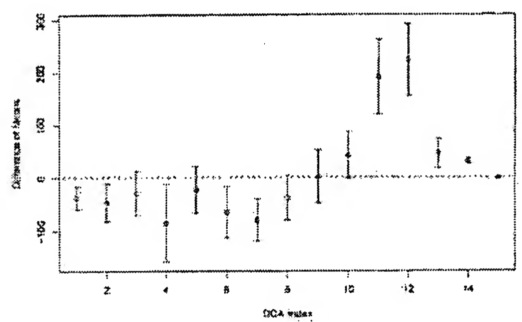
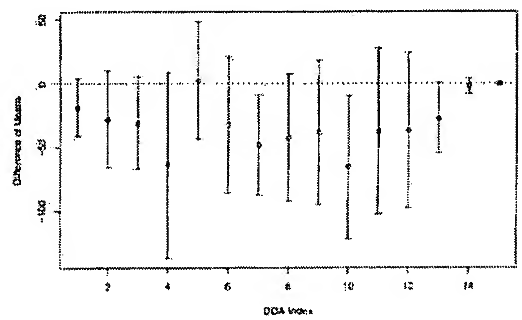


Figure 11: Difference of means 95% confidence interval for linear regression on full parameter set and final depleted parameter set



1. *blanket.counter, vdeveloper*
2. *vcorona, itm.temp, ink.conductivity*
3. *ink.density, OD100*
4. *vlight, oil.dirt, background.qualifier*
5. *vgrid, igrid, icorona, machine.temp, oil.temp, ink.temp*

4.4.1 Assessment of Insignificant Parameters

As stated above, the fact that deleting a single parameter does not significantly affect the model performance does not necessarily imply that deleting all such parameters will not affect the model performance. In fact, in the present case, deleting all the rank 5 parameters in this model leads to the difference of means plot in Figure 10.

Clearly deleting the whole set of rank 5 parameters does affect the model performance. Therefore to properly understand the significance of these parameters we need to find a way to delete them in some sensible order and view the results. At each step we shall perform the procedure detailed in the first section for obtaining a difference of means confidence interval for all the remaining rank 5 parameters. We shall split the rank 5 parameter set into 2 groups (a and b) in the following way. At step i the parameter giving the smallest sum of absolute difference of means is assigned to group a. Then confidence interval plots are obtained for all parameters not currently assigned to groups a or b. If these plots demonstrate that a parameter is significant in the performance of the model, we assign it to group b and continue until there are no unassigned parameters left.

At the end of this procedure the following four parameters were found to be insignificant: *machine.temp, igrid, oil.temp, ink.temp*. The parameters *icorona* and *vgrid* were found to be significant. As a final sanity check we fit a new full model with the whole parameter set, and a second model with the reduced set of parameters (less the four parameters deemed insignificant above). The confidence interval plot for the difference of means based on this experiment is seen in Figure 11. Clearly the reduced set of parameters does not hinder the model prediction, and in some cases may even improve the prediction, suggesting the presence of possible overfitting.

4.5 Developer voltage prediction

This is a preliminary report on the developer voltage prediction problem. Measuring and setting the developer voltage is required pre-cursor to the Indigo

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press LUT calibration procedure. It is an iterative process that consumes significant resources. We propose a statistical learning approach to this problem, with the intention of replacing the machine procedure, or at least reduce the resource consumption by supplying a "good" starting point.

As noted in the introduction, the procedure for setting the developer voltage is an iterative procedure that requires significant consumable resources. Since our goal is to reduce both consumable wastage, and machine "down-time", we wish to either replace or reduce the time and resources necessary for such procedures. In the case of developer voltage prediction, the set of measurable parameters available to us are given in Table 1.

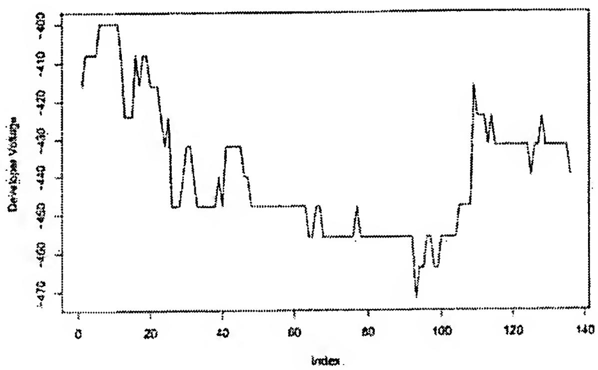
Note that the optical density 100% is not available since this is measured as part of the developer voltage calibration procedure.

We apply the same statistical learning methods employed in LUT prediction to model the developer voltage as a function of these quantities. That is, linear regression, neural networks and support vector machines. The developer voltage observations were denoised before fitting models. That is, each observation was allocated the value of the nearest 8-volt increment. This helps prevent the model from fitting noise artifacts.

The statistical learning problem associated with the prediction of developer voltage is an ordinal regression problem [8]. In this problem formulation, a function of the predictors (i.e. the press parameters) is sought that predicts the rank of the developer voltage in the range of possible developer voltages. In the case of this data, there are 19 classes, the lowest rank (class 1) being -488 volts, and the highest rank (class 19) being -344 volts. There are known linear and non-linear techniques for solving this sort of problem (see, for example [9]), however they generally require that all classes be well represented in the dataset. This is not the case with the dataset under consideration.

Therefore, we treat the problem as a simple regression problem, and then take the class nearest the model prediction as the predicted developer voltage. The fitted models interpolate in the under-represented regions and can therefore still provide predictions that should be sensible.

Figure 12: Developer Voltage for HDI-175 and Black Ink



We split the dataset into eight subsets corresponding to the two represented screens (Sequin and HDI-175) and the four represented separations for each screen (Black, Cyan, Magenta and Yellow). Figure 12 shows an example of the developer voltage values for a single screen and separation (in this case, HDI-175 and Black, respectively). For each of these subsets we apply 10-fold cross validation to fit models and obtain an independent prediction on each element in the dataset. The cross validation folds are taken from 10 randomly selected subsets that span the subset under consideration.

Using the above problem formulation we obtained developer voltage predictions on the given dataset for each of the statistical learning methods: linear regression, neural networks and support vector machines. The linear regression models included a stepwise parameter selection based on the AIC (see, for example, [10]). The neural network models had a single hidden layer with 5 hidden nodes and a non-linear output node. The support vector machine models used a radial basis function kernel, with hyper-parameters set by the parameter selection algorithm described in Staelin[5].

As stated above, the resulting predictions are

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Figure 13: Prediction Error Histograms for Different Models

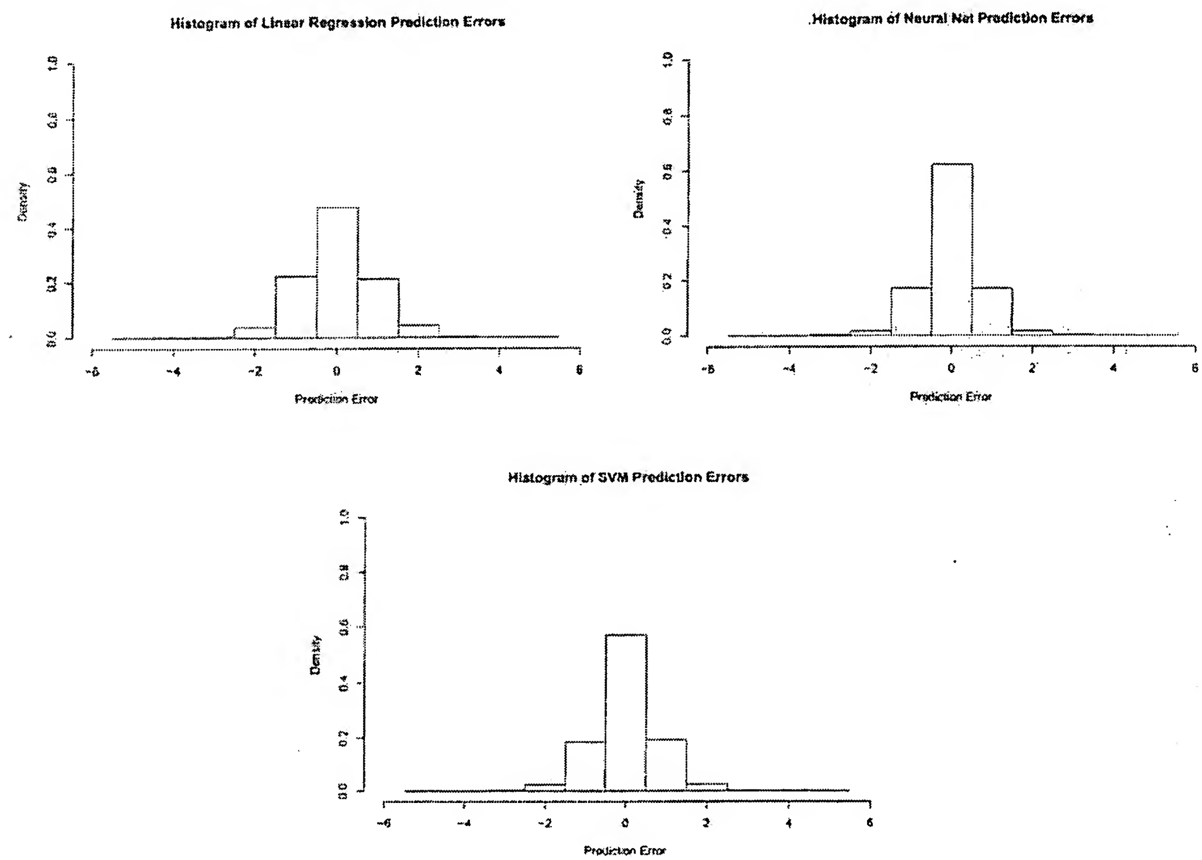

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Figure 14: Prediction Errors for Neural Network Models on HDI-175 Screen

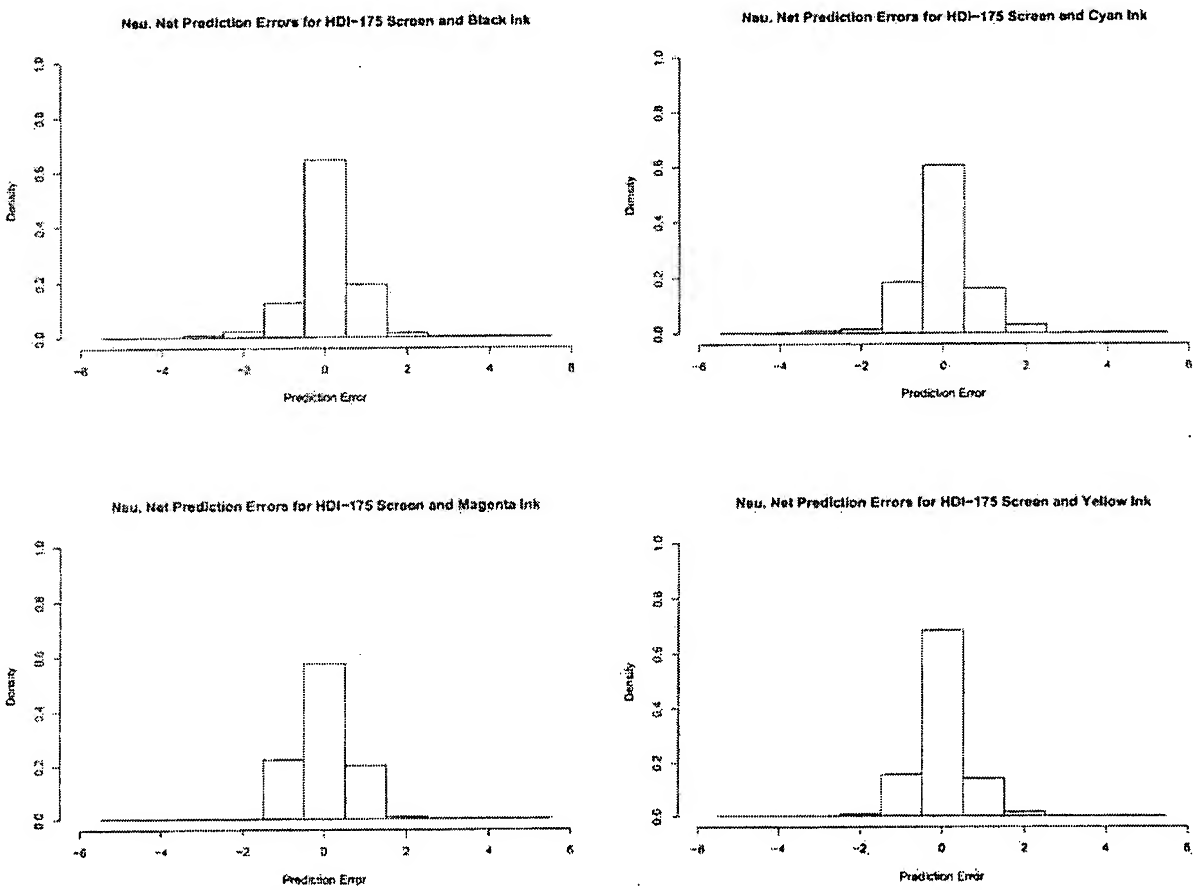

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Figure 15: Prediction Errors for Neural Network Models on Sequin Screen

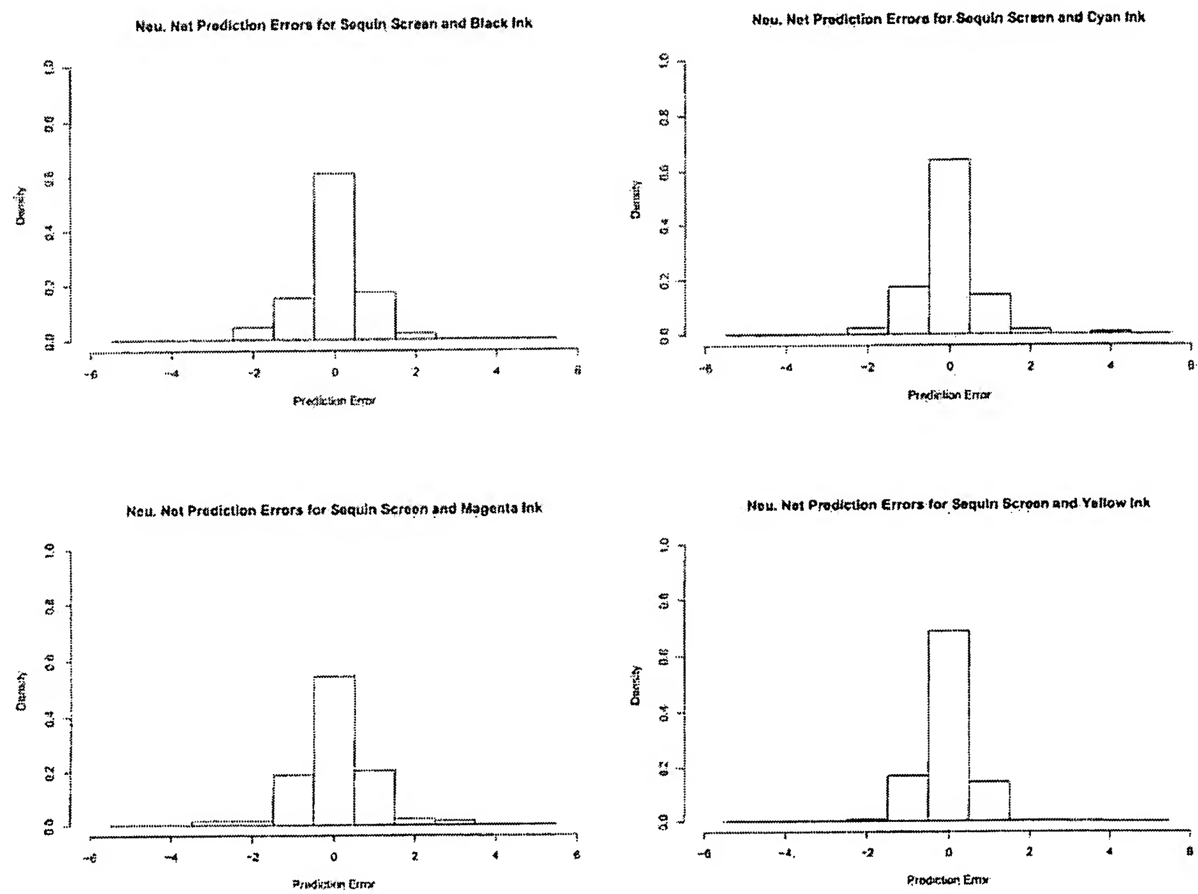

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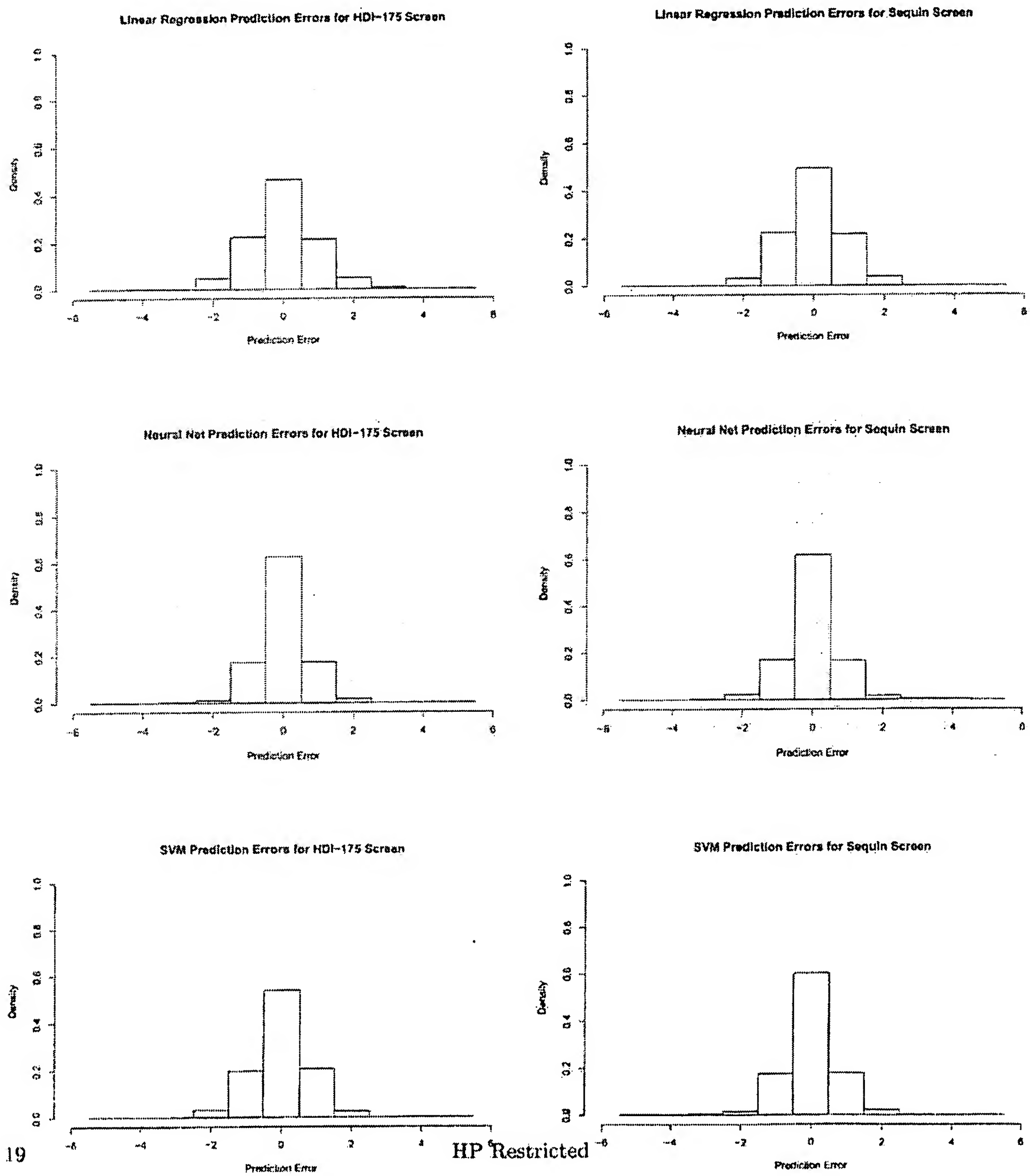
Figure 16: Prediction Error Histograms for Different Models on Different Screens



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rounded to the nearest 8-volt class. We then consider the discrepancy in number of classes between the predicted and actual values. That is, if a prediction of 432 is made when the actual class is 316, the reported error is . The histograms of the resulting prediction errors for each statistical learning method are given in Figure 13. There is also a per-screen breakdown of these graphs at the end of the article (Figure 16). In all cases the predicted voltage class is within 2 classes of the correct class for at least 99% of the predictions. For the linear regression models, the predicted class is within 1 class of the correct class at least 90% of the time, and both the non-linear methods (neural networks and svm) achieve a prediction within 1 class of the correct class at least 95% of the time, with neural networks slightly more accurate. The separation breakdown for neural network predictions and the HDI-175 screen is given in Figure 14 (Sequin screen in Figure 15). Note that the results are fairly consistent across separations.

4.6 Dot gain table prediction revisited

The results so far suggest that we can predict the developer voltage reasonably accurately given the current machine state (Section 4.5), and that given the developer voltage and OD100 and the current machine state we can predict the dot gain tables reasonably accurately (Section 4.1). The next question is whether we can predict both the developer voltage and dot gain values given just the machine state. Unfortunately, our results also suggestion that OD100 is an important parameter (Section 4.4).

Figure 17 shows the 67% and 95% prediction error confidence intervals for both HDI-175 and Sequin screens using neural networks for non-linear regression. By comparing these graphs with those in Figure 6 we can see that a noticeable deterioration in the predictions at the 95% level. This is not surprising since we have omitted two parameters that are known to be significant from the model. None-the-less the plots suggest that we can predict the dot gain LUT values to an accuracy close to Indigo's acceptance criteria even without these quantities.

Of course, the value of such an observation depends entirely on the usage model. Presumably the developer voltage needs to be calibrated from time to time to provide an acceptable optical density 100%. As demonstrated above, we can determine a suitable developer voltage using a machine learning approach. The machine would then be set to that value, and the dot gain LUT prediction could be made including developer voltage as a known parameter.

4.7 Cross-screen prediction

One of the variable quantities in the setup of the HP Indigo Press is the printing screen. The machine operator may exchange a printing screen for a different screen during printer operation. Generally this process requires recalibration of various aspects of the machine, one of which is the dot gain LUT. Supposing the machine state (temperatures, ink characteristics etc) does not change significantly during the screen exchange operation, and further that the dot gain LUT being used by the machine for the previous screen is "current" in some sense, then we may hope to discover a mapping between the dot gain LUTs for the two screens that will save some or all of the manual LUT calibration. Using the existing dot gain LUT dataset, which contains roughly equal LUT values for the Sequin and HDI-175 screens, we were able to extract a subset of 84 paired LUT measurements, in which the LUT measurements for the two screens correspond to approximately the same machine state. Each measurement includes 4 separations, giving a total of 336 paired LUT samples. Since the goal here is to discover a mapping between a LUT of one screen type and a LUT of the other screen type, we treated all separations together. This investigation is only preliminary, and certainly will require further experimentation on a larger dataset to verify the results. Figure 18 gives a plot of the printed dot area (PDA) values for one screen against the other, where each subplot corresponds to the digital dot area (DDA) given in the plot title. The apparent structure in these plots does suggest there is some relationship between the two screen LUTs, although it is quite weak in some cases.

In this investigation we shall only consider neural network models and attempt to predict the PDA for each DDA on one screen based on the whole LUT for

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Figure 17: 67% and 95% Confidence intervals with neural network prediction

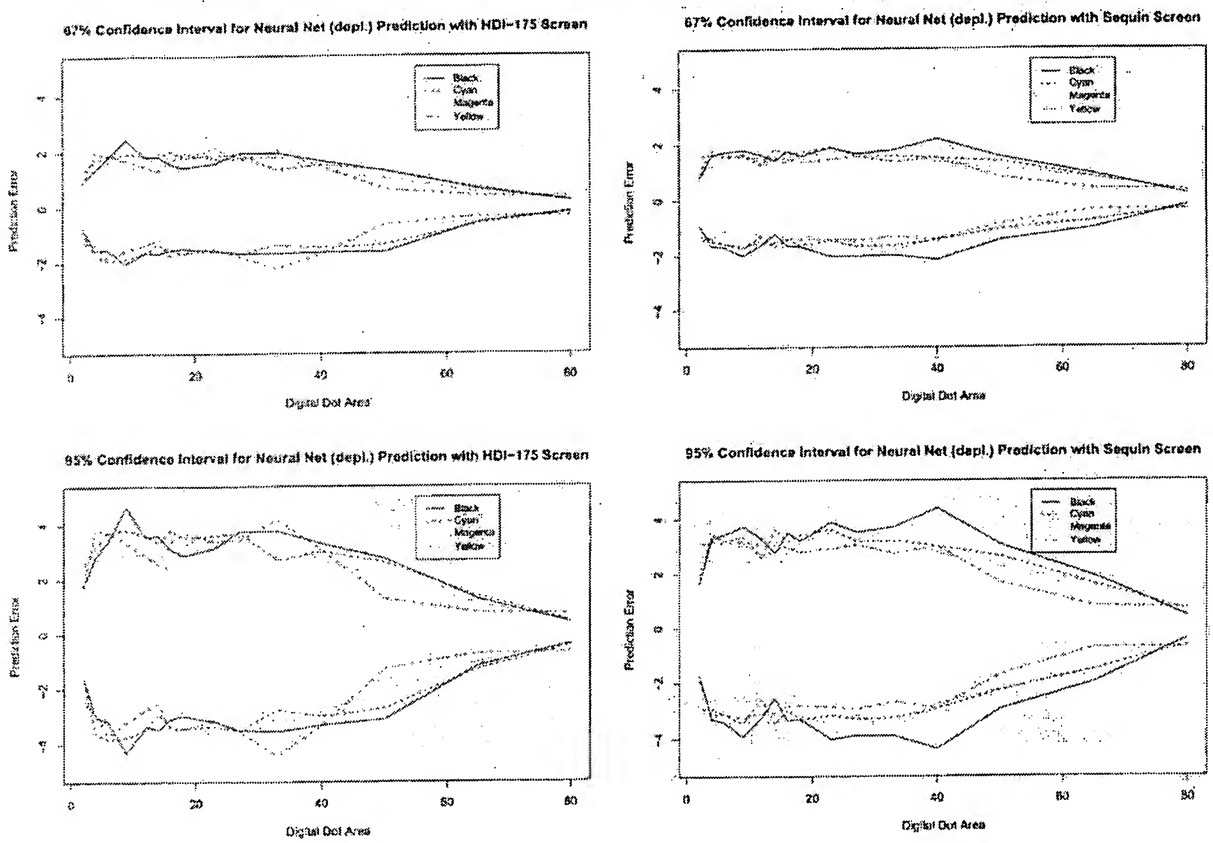

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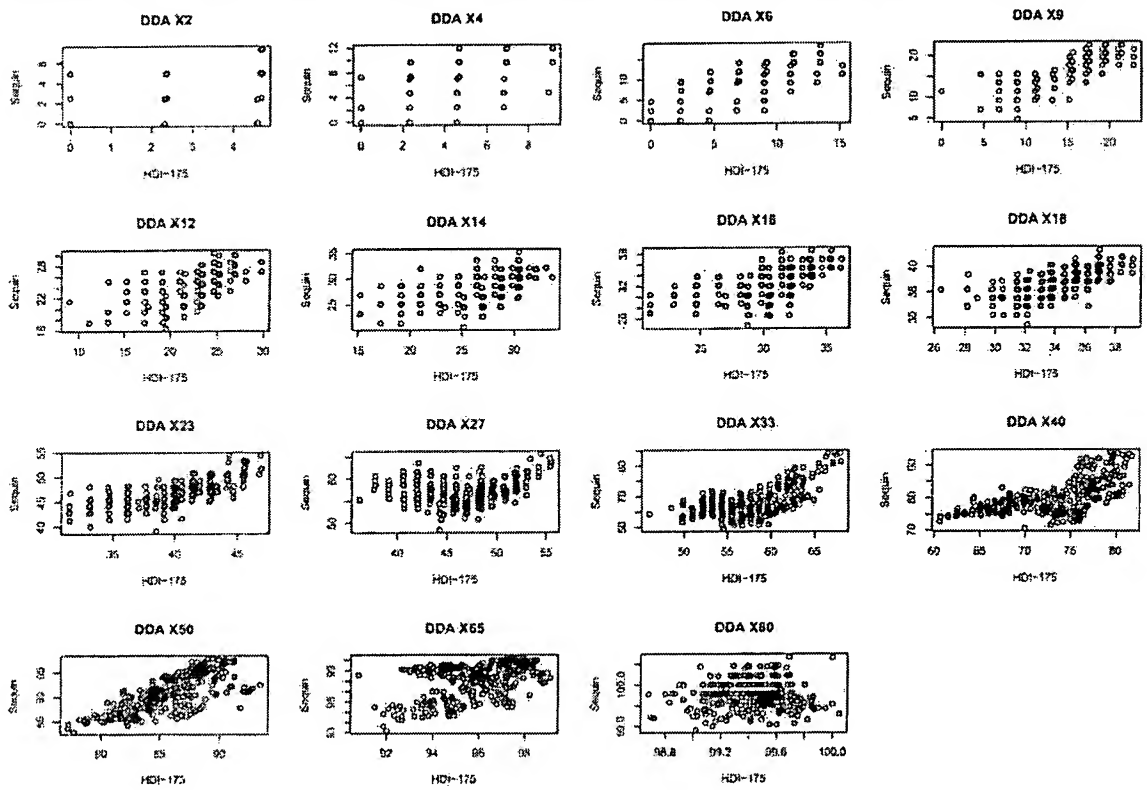
Figure 18: Scatterplots of PDA values from the Sequin Screen against PDA values from the HDI-175 Screen



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the corresponding other screen. Thus to predict the HDI-175 LUT (for example) from the Sequin LUT requires training 17 networks on the learning dataset. The same number of networks is required to perform the reverse mapping. Once again, we are interested in finding a direct mapping between LUTs from two different screens, so we do not include any extra machine state parameters in the models. We have previously shown that given the machine state, one can predict the dot gain LUT values to acceptable accuracy, so it would not be surprising to find models fitted using machine state parameters do correspondingly well. In this investigation we shall use only the dot gain LUT for one screen to predict the LUT for the other. The method used is that of the previous investigations - namely an independent prediction is obtained on each point in the dataset by using 10-fold cross validation technique. We use this prediction to assess the accuracy of the LUT fit.

The 67% and 95% confidence intervals for both comparisons (HDI->Sequin and Sequin->HDI) are show in Figure 19. In both cases the predictions fall within an absolute difference of 2 at least 67% of the time, and an absolute difference of about 4 at least 95% of the time. This meets Indigo's accuracy requirement for LUT prediction.

5 Conclusions and future work

From the initial dataset it appears that given the measurable parameters from Table 1 we can predict the various dot gain values with acceptable accuracy using linear regression. This should allow HP Indigo to greatly improve the color consistency for their presses, while reducing both the consumable waste and workflow disruption.

We are surprised to see linear regression obtain results equivalent to the non-linear learning methods (neural networks and SVM). It seems counterintuitive that the model for this problem is a linear one. We attribute the success of linear regression to the fact that the dataset was relatively small and we strongly suspect that given more data, the non-linear methods will produce better results. In future we plan to run more experiments using all three methods as we collect more data.

The set of input parameters for dot gain LUT prediction using a linear regression model may be reduced to the following subset: blanket.counter, vdeveloper, vcorona, itm.temp, ink.conductivity, ink.density, OD100, vlight, oil.dirt, background.qualifier,vgrid, icorona. That is, the following four parameters were found to not significantly affect the model performance: igrid, machine.temp, oil.temp, ink.temp. It is difficult to determine the relative importance of the input parameters since single deletions do not account for parameter interactions. Still, as a rough indicator we would suggest the following initial ranking:

1. *blanket.counter, vdeveloper*
2. *vcorona, itm.temp, ink.conductivity*
3. *ink.density, OD100*
4. *vlight, oil.dirt, background.qualifier*
5. *vgrid, icorona*

This introductory study of the developer voltage prediction problem suggests that we are able to predict the developer voltage given the machine state parameters with a high degree of accuracy. In particular, if an error of at most one 8-volt step is acceptable, then statistical learning methods can supply acceptable predictions more than 95% of the time. On the other hand, if an exact value is demanded, the models investigated here can give a starting point that will be accurate approximately 60% of the time, at most 1 step off approximately 95% of the time, and at most 2 steps off approximately 99% of the time. This is likely to yield significant savings in consumables and calibration time for users of the Indigo press.

These results are obtained on a relatively small dataset, operated with only 2 screens and a single substrate type. The conclusions obtained here should be verified on a much larger data sample, or alternatively as an experimental implementation on a functioning press. Future work, based on a larger dataset, may yield more accurate results as the more appropriate ordinal regression models could be utilized.

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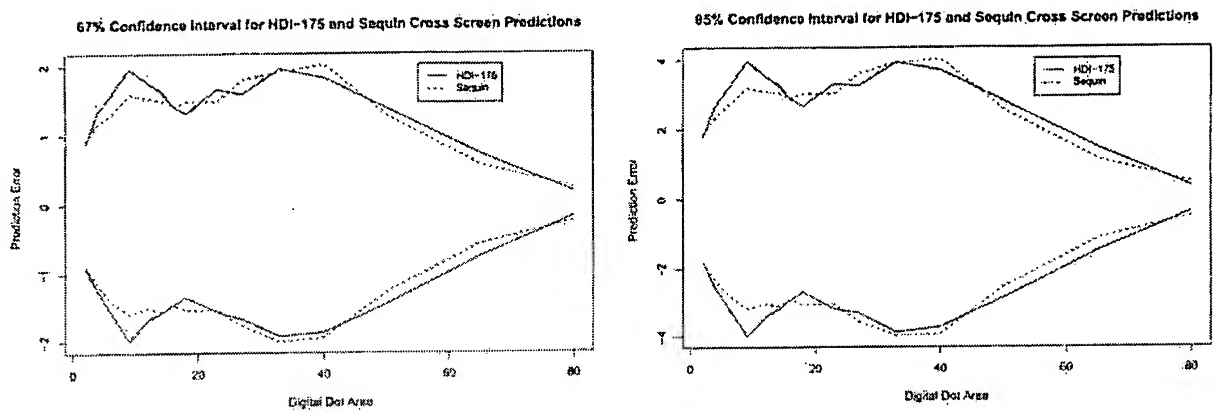

Figure 19: Prediction Error 95% Confidence Intervals for Cross-screeb Prediction Using Neural Networks

A number of questions need to be addressed before this can be sent to customers' presses. For example, we will need to evaluate the best update interval, e.g. how often should the system update the dot gain tables using model-based prediction with no printed measurements? How often should we use the "fast calibration" to get more accurate predictions? How often do we need to do full calibrations? How often should we update or refit the models to incorporate information from full calibrations? Other questions regard cross-machine measurement and prediction. For example, are individual presses idiosyncratic, or can we use measurements from one machine to predict the behavior of another machine?

Since the first step in the calibration process involves an iterative process to set the developer voltage, can we either predict the correct developer voltage setting directly, or can we use the prediction to get more accurate initial conditions for the iterative search?

Over the next several months we expect to prototype a dot gain prediction system that is embedded in a press. We can them begin conducting various experiments to evaluate the actual improvement in color consistency when compared to the current practice of sporadic LUT calibrations.

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